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Research Paper

Mathematical Modeling and Optimization of Milling Parameters in AA 5083 Aluminum Alloy

Gökhan Başar[1*], Funda Kahraman[2], Ganime Tuğba Önder[3]

[1]Osmaniye Korkut Ata University, Faculty of Engineering, Osmaniye, Turkey
[2]Tarsus University, Faculty of Technology, Mersin, Turkey
[3]Cukurova University, Adana Vocational High School, Adana, Turkey

Abstract

An experimental study was carried out to determine the effect of different cutting parameters such as feed, spindle speed and depth of cut on surface roughness in face milling of 5083 aluminum alloy. The mathematical model was developed to estimate surface roughness using Response Surface Methodology. The significant contribution of cutting parameters was detected by analysis of variance. Statistical analysis indicated that feed and spindle speed have the most considerable influence on surface roughness. After developed mathematical model, desirability function analysis was performed to minimize the surface roughness. The lowest surface roughness (0.41 µm) was acquired at a feed of 3008 mm/min, a spindle speed of 5981 rpm and a depth of cut of 0.54 mm.

Keywords: Response surface methodology, desirability function analysis, face milling, aluminum.

1. INTRODUCTION

The main purpose of chip removal process is to achieve the desired geometric and dimensional tolerance and a precise surface on the workpiece. Machining process like milling has been mostly used in the machine-manufacturing, automotive and aircraft industries. Using the milling process, machine parts with the desired dimensional tolerance and surface quality can be machined on planar, oblique, circular and various profile surfaces. It is high productivity since the cutting tools have more than one insert [1]. Surface quality is crucial for engineering materials. The surface roughness is an indication of the surface quality of the machined materials. It depends on workpiece, cutting conditions, tool material and geometry [2]. Improvement of surface quality increases the fatigue strength, abrasion and corrosion resistance of the material. Therefore, cutting parameters should be selected to achieve the required surface quality. Surface roughness is commonly considered as a major manufacturing goal for machining processes in many of the existing research works [3-5].

Nowadays, statistical techniques like response surface methodology (RSM), desirability function analysis (DFA), Taguchi method (TM) and genetic algorithm have been used to determine optimum cutting parameters in machining processes. The studies conducted in the literature on this subject can be summarized as follows.

Pradhan et al. [6] used DFA to examine the influences of cutting speed, feed and depth of cut on different types of surface roughness in the machining of conventional cast Al/SiCp composites in turning. Esme [7] utilized desirability function combined with RSM to optimize the surface roughness. Using RSM, he developed a mathematical model with cutting parameters. The results indicated that feed was a crucial factor on surface roughness. Fnides et al. [8] used RSM and DFA based optimizations to find the optimum cutting conditions of minimum surface roughness and maximum material removal rate in face milling of AISI 1040 steel. Palanisamy et al. [9] experimented for milling of T6-6061 aluminium alloy to optimize cutting conditions using RSM. The results indicated that the speed and feed are important factors for improved minimum surface roughness. Güvercin and Yıldız [10] investigated the influences of cutting parameters on surface roughness of AISI 1040 steel. Experimental analysis was performed by RSM. Kıvak [11] searched influence of input variables on surface roughness and flank wear in milling process using TM and regression analysis (RA). Vardhan et al. [12] conducted TM and RSM for modeling and optimization of surface roughness and material removal rate. Sarıkaya et al. [13] used TM to examine the effects of machining parameters on surfa-

* Corresponding authour
Email: gokhanbasar@osmaniye.edu.tr

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ce roughness and tool life of AISI D3 steel in face milling process. Basar et al. [14] modeled and optimized the surface roughness in face milling using TM and RA. Fedai et al. [15] used multi-objective Taguchi Technique to multi-response optimization of input variables on face milling of AISI 4140 steel with PVD TiAlN/TiN coated carbide inserts. Gaitonde et al. [16] researched the effect of input parameters on cutting force, surface roughness and temperature in hard milling using RSM. Elkhabeery et al. [17] investigated the influence of input variables on the surface roughness, cutting force and material removal rate of AA 5083 aluminum alloy in CNC end milling using RSM. Ariffin et al. [18] modeled and optimized input variables for surface roughness, temperature and tool wear of A319 aluminum alloy by using central composite design based RSM. Arjun et al. [19] studied the effect of input variables on surface roughness and material removal rate in milling of aluminum 7075 alloy by using Box-Behnken design in RSM. They developed mathematical models for output variables.

This study was examined statistically and experimentally in face milling of 5083 aluminum alloy. The predictive model of the surface roughness was obtained by RSM. DFA was used to optimize cutting parameters with the lowest surface roughness.

2. EXPERIMENTAL PROCEDURES

The experiments were performed using Mitsubishi M70 CNC vertical milling center equipped with a ϕ 40 mm face milling cutter. Wet face milling process was conducted on AA 5083 aluminum alloy using boron oil as cutting fluid with APGT 1604 Korloy milling inserts (Figure 1). Surface roughness values were measured with MITUTOYO SJ-400.

Figure 1. Experimental set up for milling

RSM was used for designing and analysing experiment by using The Design of Expert software. RSM was used to obtain a mathematical model of response as a function of the feed (f), spindle speed (v) and depth of cut (doc). The levels of input factors were shown in Table 1. The relationship between the actual and coded factors was calculated using Equation (1).

Table 1. Levels of the factors

Factors/Levels	-1	0	1
f (mm/min)	2000	3000	4000
v (rpm)	4000	5000	6000
doc (mm)	0.5	1	1.5

$$x_1 = \frac{f-3000}{1000}, \quad x_2 = \frac{v-5000}{1000}, \quad x_3 \frac{doc-1}{0.5} \tag{1}$$

with x_1 is coded factor that symbolizes f, x_2 is coded factor that symbolizes v, x_3 is coded factor that symbolizes doc.

3. RESULTS AND DISCUSSION

3.1 Prediction of Surface Roughness using RSM

RSM used to determine the relationship between dependent and independent variables. It is also used as a mathematical equation of independent variables to predict dependent variables. The model is depended on the investigation of the response surface obtained with the results of the experimental design based on the lower and upper levels of the factors [20]. The first order and second-order model polynomial model is expressed by Equation (2) and (3), respectively.

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \varepsilon \tag{2}$$

$$y = \beta_0 + \sum_{j=1}^{k} \beta_i x_j + \sum_{j=1}^{k} \beta_{ij} x_j^2 + \sum_{i}^{k-1} \sum_{j}^{j} \beta_{ij} x_i x_j + \varepsilon \tag{3}$$

where y: response, β_0: constant, $\beta_1, \beta_2, ..., \beta_k$: regression coefficient, $x_1, x_2, ..., x_i$: input factors, k: number of input factors, $i = 1, 2, ..., k-1$ and, $j = 1, 2, ..., k$, ε: random error.

Model statistics are given in Table 2. Among the models in Table 2, the most suitable model is the quadratic model.

Table 2. Model statistics

Source	Std Dev.	R^2	Adj-R^2	
Linear	0.14	0.7389	0.6900	
Quadratic	0.097	0.9238	0.8551	Suggested
Cubic	0.029	0.9957	0.9865	Aliased

Face-centered cubic design (FCD) was used for developing the mathematical model. The model supplying relation among surface roughness and cutting parameters was created. The model was set up based on Equation (4) in terms of coded factors.

$$\begin{aligned} Ra &= 0.66 + 0.22 \cdot x_1 - 0.21 \cdot x_2 + 0.035 \cdot x_3 - 0.100 \cdot x_1 \cdot x_2 + 0.030 \cdot x_1 \cdot x_3 \\ &+ 0.033 \cdot x_2 \cdot x_3 + 0.15 \cdot x_1^2 + 0.011 \cdot x_2^2 + 5.909E-003 \cdot x_3^2 \end{aligned} \tag{4}$$

The actual and predicted surface roughness values based on the RSM with FCD were presented in Table 3. Predicted versus experimental values of surface roughness was shown in Figure 2. According to Figure 2, the agreement between actual and predicted values was high. Determination coefficient (R^2) between actual results and estimated values was acquired as 92 %. It indicated that mathematical model fits well with actual test results. The comparisons of actual test results with the model estimations were demonstrated in terms of mean absolute percentage error (MAPE). The MAPE was found to be 7.10 %. This value was enough low to verify the superior predictive power of model.

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Table 3. Experimental and predicted surface roughness values for FCD

Std	Run	f (mm/min)	v (rpm)	doc (mm)	Actual Ra (μm)	Predicted Ra (μm)
1	20	2000	4000	0.50	0.73	0.74
2	10	4000	4000	0.50	1.40	1.31
3	16	2000	6000	0.50	0.46	0.47
4	12	4000	6000	0.50	0.55	0.64
5	15	2000	4000	1.50	0.78	0.69
6	19	4000	4000	1.50	1.39	1.38
7	5	2000	6000	1.50	0.46	0.54
8	3	4000	6000	1.50	0.85	0.83
9	11	2000	5000	1.00	0.6	0.59
10	14	4000	5000	1.00	1.00	1.02
11	13	3000	4000	1.00	0.70	0.87
12	6	3000	6000	1.00	0.62	0.46
13	9	3000	5000	0.50	0.65	0.63
14	7	3000	5000	1.50	0.66	0.70
15	8	3000	5000	1.00	0.66	0.66
16	17	3000	5000	1.00	0.65	0.66
17	18	3000	5000	1.00	0.63	0.66
18	2	3000	5000	1.00	0.64	0.66
19	1	3000	5000	1.00	0.70	0.66
20	4	3000	5000	1.00	0.70	0.66
MAPE:						7.10 %

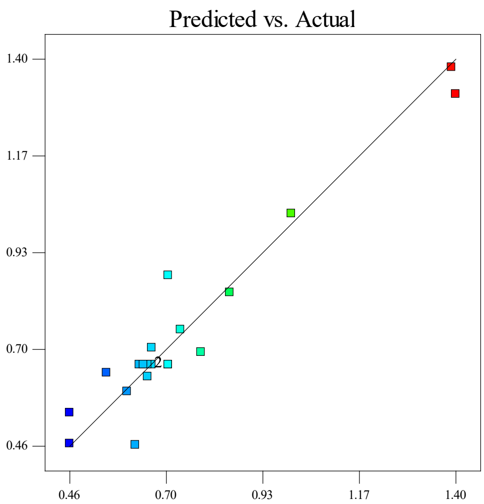

Figure 2. Plot of predicted against experimental results

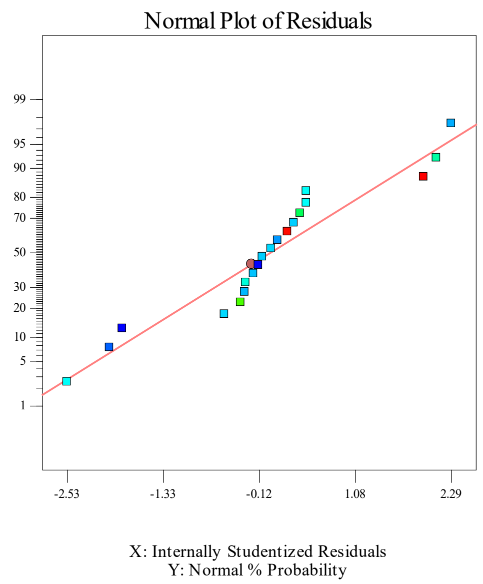

Figure 3. The normal probability plot of the residuals

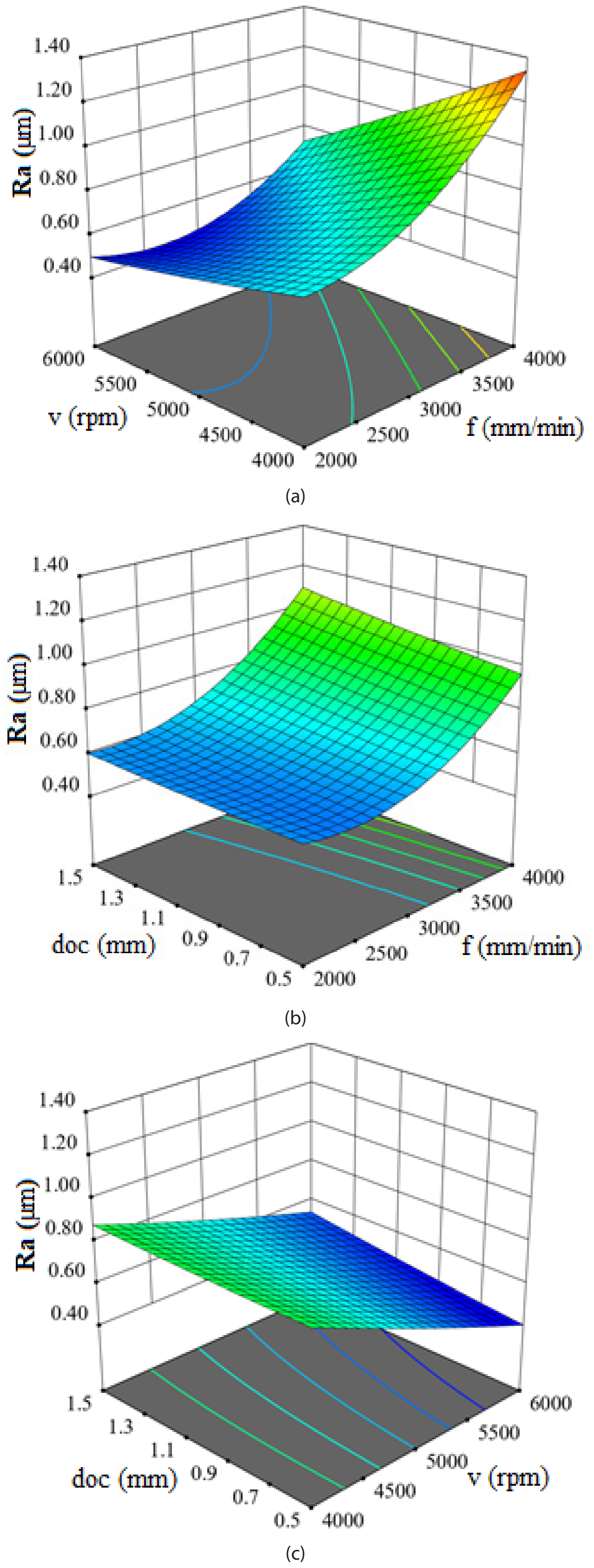

Figure 4. a) Interaction of f (mm/min) and v (rpm), b) Interaction of f (mm/min) and doc (mm), c) Interaction of v (rpm) and doc (mm)

The normal probability plot of the residuals was indicated in Figure 3. It indicates that the residuals usually fall down a straight line meaning that the errors are scattered ordinarily.

Figure 4 (a-c) shows the interaction effect cutting parame-

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ters on the surface roughness. The 3D surface plots show that the surface roughness value decreases as the feed rate decreases and the cutting speed increases. It is seen that the depth of cut does not have a significant effect on surface quality.

Analysis of variance (ANOVA) was performed to test the applicability of improved model for the experimental data fitted in the model or not. ANOVA was used to find the importance of the factor effects based on 95 % confidence level. ANOVA results were demonstrated in Table 4. x_1, x_2, x_1x_2, x_1^2 are considerable model terms. Other model terms are not considerable.

Table 4. ANOVA results for Ra

Source	SS	DoF	MS	F-value	p-value
Model	1.13	9	0.13	13.46	0.0002
	0.47	1	0.47	50.07	< 0.0001
	0.42	1	0.42	45.54	< 0.0001
	0.012	1	0.012	1.31	0.2783
	0.080	1	0.080	8.59	0.0150
	7.200E-003	1	7.200E-003	0.77	0.4000
	8.450E-003	1	8.450E-003	0.91	0.3634
	0.063	1	0.063	6.72	0.0268
	3.273E-004	1	3.273E-004	0.035	0.8551
	9.602E-005	1	9.602E-005	0.010	0.9212
Residual	0.093	10	9.318E-003		
Total	1.22	19			
R-Squared	0.9238				

3.2 Optimization using DFA

After developing the mathematical model, DFA described by Derringer and Suich can be used to optimize the response. Single response optimization detects how input parameters affect desirability of individual response. DFA is also used control variables to find the best combination of control variables in the combined approach of RSM [21, 22].

In this analysis, the goal used for the surface roughness was "minimize" and the goal used for the control factors was "within range". The individual desirability (d_i) for smaller the better was given in Equation (5).

$$d_i = \begin{cases} 1, & y_i \le y_{\min} \\ \left(\dfrac{y_{\max} - y_i}{y_{\max} - y_{\min}}\right)^r, & y_{\min} < y_i < y_{\max} \\ 0, & y_i \ge y_{\max} \end{cases} \tag{5}$$

$y_{\min}$, y_i and $y_{\max}$ denominate lower value, response and upper value, respectively. r is detected with respect to the need of the user.

Table 5. The range of input variables and response

Constraints	Target	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
f	range	2000	4000	1	1	3
v	range	4000	6000	1	1	3
doc	range	0.5	1.5	1	1	3
Ra	minimize	0.46	1.4	1	1	5

The range of input variables and response was indicated in Table 5. Table 6 indicated repetitive specification of optimal parameter. The reached maximum desirability of 1 means that it is possible to meet surface roughness value. The lowest value of surface roughness (0.41 μm) was acquired as 3008 mm/min feed, 5981 rpm spindle speed and 0.54 mm depth of cut.

Table 6. Repetitive specification of optimal parameter

	Cutting parameters				
Solutions	f (mm/min)	v (rpm)	doc (mm)	Ra (μm)	Desirability
1	3008	5981	0.54	0.41	1.000
2	2857	5937	0.62	0.42	1.000
3	3071	5946	0.51	0.42	1.000
4	2806	6000	1.13	0.46	0.997

4. CONCLUSION

The research offered a face-centered cubic design combined with RSM to develop a mathematical model to estimate surface roughness. The optimal cutting parameters were determined by using DFA. Results from the experimental study were given below:

- The accomplishment of the model has been appraised by ANOVA, which appoints important 92%. With respect to ANOVA result, the feed and spindle speed are the most important parameters which decrease surface roughness.
- The MAPE between actual and estimated values was computed as 7.10 %.
- Minimum surface roughness parameters were obtained as 3008 mm/min feed, 5981 rpm spindle speed and 0.54 mm depth of cut by using DFA.

Note: This research was presented at the 3rd International Mediterranean Science and Engineering Congress, IMSEC 2018 (24-26 October 2018, Adana, Turkey).

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